A PROPOSED ARTIFICIAL NEURAL NETWORK MODEL for PEM FUEL CELLS

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Abstract

Fuel cells convert the chemical energy directly to the electrical energy and hence they are a very favorable alternative energy source. In the literature, there are many studies related to the modeling of fuel cells. Artificial neural networks (ANNs) is one of the promising techniques for modelling nonlinear systems such as fuel cells. The proposed model in this study doesn't require many parameters like other studies. Firstly, training and testing data was obtained the dynamic model of a PEM fuel-cell. Then, proposed ANN model outputs are compared with dynamic model ouputs Simulation results shows that the proposed ANN model can be used very efficiently for PEM fuel-cells without using many parameters.

1. Introduction

Due to the rapid depletion of fossil fuels and the increase in energy demand, the study of alternative energy sources has increased rapidly. [1]

Fuel cells are an alternative technology for energy sources which use hydrogen as a fuel. They are high efficiency conversion systems and these systems produce electricity from hydrogen energy. Fuel cells generate energy by the electrochemical reaction of hydrogen and oxygen [2]. Proton exchange membrane fuel cell (PEMFC) technology is the significant candidate in fuel cell technology due to its high-power density, operation at low temperatures, long cell and stack life [3]. The output voltage of PEM fuel cells is affected by many parameters such as operating temperature, pressure and humidification. In order to improve fuel cell performances, it is essential to understand these parametric effects on fuel cell operations [4].

Due to the complex electrochemical events occurring in a cell, obtained models are quite non-linear. Because of the achievements of the design of non-linear systems, artificial neural networks is a powerful tool for modeling. Artificial neural networks can learn from a set of input–output data without the need of full parameters of the fuel cell system. In the literature, many studies have existence modeling of fuel cells using artificial neural networks. Hatti et al. [5] investigated the static behaviour of the PEMFC taking into different stoichiometric conditions using artificial neural networks. Vicky Rouss et al.[6] investigated nonlinear mechanical behavior of the fuel cell modeled using artificial neural Networks. In [7], ANN model was developed taking into account the transient behavior of the fuel cell.

In this paper, a novel Artificial Neural Network (ANN) based model is proposed for PEMFCs. Training data of the ANN model are obtained from dynamic model of the PEM fuel cell (D-PEMFC). The D-PEMFC, previously used in many studies, is realized MATLAB/Simulink. The proposed ANN model is simple and doesn't require many parameters such as presented in the literature.

It requires only fuel cell current and voltage data that include instantaneous value of voltage ($k\lambda$), additional three values of voltages which are obtained namely at $(k-1)\lambda$, $(k-2)\lambda$ and $(k-3)\lambda$ (λ is sampling time), and also sequential voltage differences.

2. Fuel Cells

Fuel cells are conversion systems that convert chemical energy into electrical energy by use of chemical reaction. Fuel cell is efficient, quiet and environmentally friendly power generation system [8]. Also, fuel cells don't have to mechanical components so the losses and noise caused by them are eliminated. Proton exchange membrane fuel cell (PEMFC) is well-known fuel cell type due to its high efficiency and fast start up [9]. PEM fuel cell consists of two electrodes (anode and cathode) and the membrane which separates electrodes (Figure 1). The chemical reactions occurring at the electrodes of a fuel cell are as follows:

$$\begin{aligned}&\text{Anode reaction: } 2H2 \rightarrow 4H+ +4\ e- \\ &\text{Cathode reaction: } O2 + 4H+ + e- \rightarrow 2H2O \qquad (1)\\ &\text{Total cell reaction: } 2H2 + O2 \rightarrow 2H2O + \text{electricity} + \text{heat}\end{aligned}$$

The products of this process are water, DC electricity and heat [10].

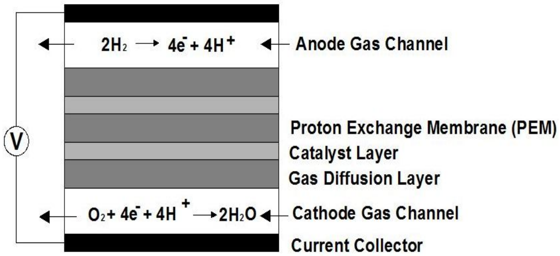

Fig. 1. Schematic of proton exchange membrane fuel cells

Figure 2 shows a typcial polarisation curve which is generally used to express the characteristics of a fuel cell. Performance of the fuel cell voltage depends on many variables such as current, temperature, pressure, fuel cell dimensions and stoichiometry of the inlet gases [11]. When the current increases, output voltage of fuel cell decreases. In general, PEM fuel cell has the best performance at temperatures around 70-80 ºC [12].

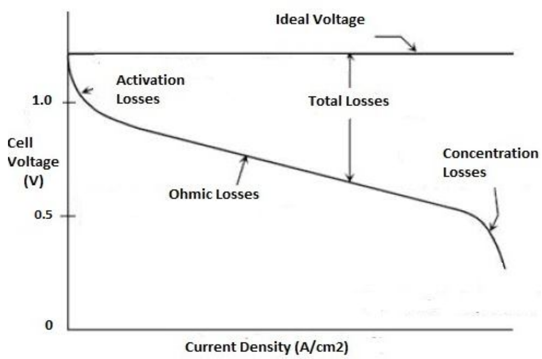

Fig. 2. Polarisation curve of fuel cell

The D-PEMFC model used in this paper is realized in MATLAB/Simulink (Figure 3). In this study, D-PEMFC is realized in MATLAB/Simulink program. D-PEMFC consists of one string of 88 cells connected in series. A cell voltage is assumed to be approximately 0.7 V, output voltage of the PEMFC system is calculated as 0.7x88 = 61.6 V. All the parameters of equations are given in Table 1.

The relationship between partial pressure of hydrogen and molar flow of any gas (hydrogen) can be expressed as;

$$\frac{q_{H_2}}{p_{H_2}} = \frac{K_{an}}{\sqrt{M_{H_2}}} = K_{H_2} \tag{2}$$

Hydrogen molar flow is defined hydrogen input flow, hydrogen output flow and hydrogen flow during the reaction. This definition can be expressed as;

$$\frac{d}{dt} p_{H_2} = \frac{RT}{V_{an}}\left(q_{H_2}^{in} - q_{H_2}^{out} - q_{H_2}^{r}\right) \tag{3}$$

According to the basic electrochemical relationship between fuel cell current and hydrogen flow, hydrogen flow rate in reaction can be expressed with equation (3);

$$q_{H_2}^{r} = \frac{N_0 I_{FC}}{2F} = 2K_r I_{FC} \tag{4}$$

When we use the Laplace transforms of equation (1) and (2), the hydrogen partial pressure can be obtained in the s domain as;

$$p_{H2} = \frac{1/K_{H2}}{1+\tau_{H_2} s}(q_{H_2}^{in} - 2K_r I_{FC}) \tag{5}$$

where

$$\tau_{H_2} = \frac{V_{an}}{K_{H_2} RT} \tag{6}$$

Similarly, the partial pressure of oxygen and water can be obtained. When we assumed that temperature, oxygen concentration and output voltage of the fuel cell system constant, it can be expressed by the following equation [13,14].

$$V_{cell} = E + \eta_{act} + \eta_{ohmic} \tag{7}$$

In this expression, E is the theoretical voltage produced by Nerst equation

$$E = N_0\left[E_0 + \frac{RT}{2F} log\left[\frac{p_{H_2}\sqrt{P_{o_2}}}{p_{H_2O}}\right]\right] \tag{8}$$

where

η_{act} , activation losses

$$\eta_{act} = -B\,ln(C\,I_{FC}) \tag{9}$$

η_{ohmic} , ohmic losses

$$\eta_{ohmic} = -R^{int} I_{FC} \tag{10}$$

The amount of hydrogen in the hydrogen tank is defined as

$$q_{H_2}^{req} = \frac{N_0 I_{FC}}{2FU} \tag{11}$$

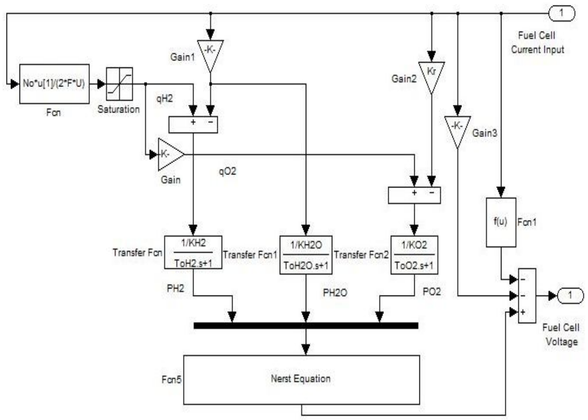

Fig. 3. Dynamic model of the PEM fuel cell

Table 1. Parameters of the fuel cell equations

Name	Defining of the parameter
B,C	Constant [A^{-1}] and [V]
E	Nernst instantaneous voltage [V]
E_0	No load voltage [V]
F	Faraday's constant [C (kmol)-1]
I_{FC}	Fuel cell current [A]
K_{an}	Anode valve constant [$\sqrt{kmolkg}$ (atm s)$^{-1}$]
K_{H2}	Hydrogen valve molar constant [kmol (atm s)$^{-1}$]
K_{H2O}	Water valve molar constant [kmol (atm s)$^{-1}$]
K_{O2}	Oxygen valve molar constant [kmol (atm s)$^{-1}$]
K_r	Modeling constant [kmol (s A)$^{-1}$]
M_{H2}	Molar mass of hydrogen [kg (kmol)$^{-1}$]
N_0	Number of series fuel cell in the stack
P_{H2}	Hydrogen partial pressure [atm]
P_{H2O}	Water partial pressure [atm]
P_{O2}	Oxygen partial pressure [atm]
q_{O_2}	Input molar flow of oxygen [kmol (s)-1]
$q_{H_2}^{in}$	Hydrogen input flow [kmol (s)-1]
$q_{H_2}^{out}$	Hydrogen output flow [kmol (s)-1]
$q_{H_2}^{r}$	Hydrogen flow that reacts [kmol (s)-1]
η_{ohmic}	Ohmic over voltage [V]
R	Universal gas constant [(1 atm) (kmol K)-1]
R_{int}	Internal resistance of fuel cell [Ω]
T	Absolute temperature [K]
U	Utilization rate
V_{an}	Volume of anode [m^3]
V_{cell}	Dc output voltage of fuel cell system [V]
τ_{H_2}	Hydrogen time constant [s]
τ_{O_2}	Oxygen time constant [s]
τ_{H_2O}	Water time constant [s]
η_{act}	Activation over voltage [V]
$q_{H_2}^{req}$	Amount of hydrogen flow required to meet the load change [kmol (s)-1]

3. Artificial Neural Networks

Artificial Neural Networks simulate working principles of the human brain. Due to the parallel operation structure, computation and information processing competence of artificial neural network is quite successful. ANNs is favourable technique in order to solve a variety of problems in pattern recognition, prediction, optimization and control [15,16].

3.1. Preparing of the Artificial Neural Networks Data

Training data of the proposed ANN-PEMFC model was obtained from D-PEMFC with sampling time 0.2 s. In order to obtain data sets, D-PEMFC model is simulated with different power values. Figure 4 shows input-output data of the D-PEMFC. As shown Figure 4, when current data increased or decreased suddenly, output voltage is decreased or increased, accordingly.

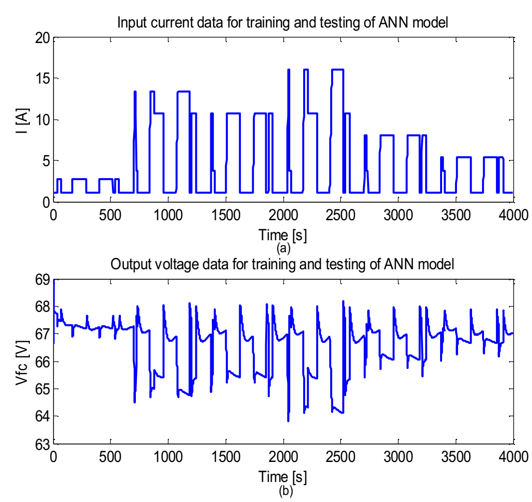

Fig. 4. (a) Input current (b) output voltage data for training and testing of ANN model

3.2 The proposed Artificial Neural Networks Model

The proposed model's inputs are fuel cell current data (I_{FC}), one sampling delayed fuel cell current data, three sampling delayed fuel cell voltages data (U_{FC}), and sequential voltage and current differences. Inputs of the proposed ANN-PEMFC model is given as follows,

I. Input $I_{FC}[(k)\lambda]$

II. Input $U_{FC}[(k-1)\lambda]$

III. Input $U_{FC}[(k-2)\lambda]$

IV. Input $U_{FC}[(k-3)\lambda]$ (12)

V. Input $U_{FC}[(k-1)\lambda]-U_{FC}[(k-2)\lambda]$

VI. Input $(U_{FC}[(k-1)\lambda]-U_{FC}[(k-2)\lambda])-(U_{FC}[(k-2)\lambda]-U_{FC}[(k-3)\lambda])$

VII. Input $I_{FC}[(k-1)\lambda]$

VIII. Input $I_{FC}[(k)\lambda]-I_{FC}[(k-1)\lambda]$

In order to model ANN-PEMFC, a multilayer feedforward ANN back-propagation with Levenberg-Marquardt training algorithm is used in this paper. This algorithm is very efficient, fast and easy to implement. Levenberg-Marquardt algorithm is an approximation to Newtons's method. The update weight vector can be expressed as;

$$w_{ji}(k+1)=w_{ji}(k)-\left[J^T J+\lambda I\right]^{-1} J^T E \tag{13}$$

In equation (13), $w_{ji}(k+1)$ is a update weight vector, $w_{ji}(k)$ is a weight vector, J is a Jacobian matrix, λ is algorithmic parameter, I is a identity matrix and E is a error vector. If algorithmic parameter is selected small value, equation (13) becomes a Gauss-Newton update. On the other hand, algorithmic parameter is selected large value; it becomes a gradient descent update [17]. The ANN consists of fully connected four layers network with two hidden layers. The input layer consists of eight inputs. Each hidden layer has eighteen neurons with tansig activation function. The output layer has one neuron with purelin activation function. The structure of the proposed ANN-PEMFC model is shown in Figure 5.

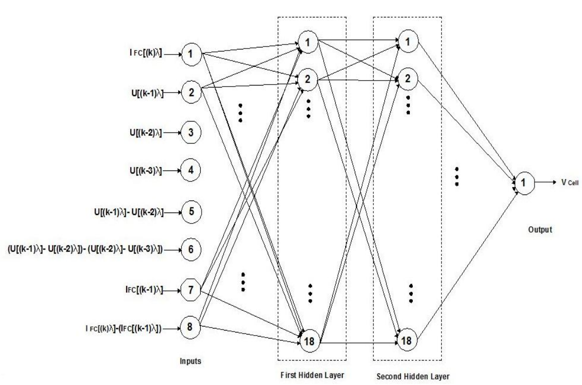

Fig. 5. Structure of the proposed network

The data set obtained MATLAB/Simulink used to train and test the proposed ANN model. Figure 4 shows this data set which consist two parts. The training set is selected between interval of t=0 to 2000 s and t=3201 to 4000 s. The test data is selected within the interval of t=2001 to 3200 s.

4. Test and Results

Relative error is calculated between the D-PEMFC and ANN-PEMFC using by equation to test achievement of the proposed model.

$$\%e = \frac{|V_{D-PEMFC} - V_{ANN-PEMFC}|}{V_{D-PEMFC}} x\ 100 \tag{14}$$

Figure 6-7 shows that output voltage for training ANN-PEMFC, D-PEMFC, relative error of the models, respectively. Maximum relative error of training is calculated as % 0.26. The performance of output voltage for testing ANN-PEMFC, D-PEMFC models and relative error are shown in Figure 8. Also, maximum relative error of testing is calculated as % 2.75. The results shown in Figure 6-7-8 denote that the proposed ANN-PEMFC model and D-PEMFC model results have similar behavior in terms of voltage. This result exhibit that the proposed model can be used accurately estimates the output voltage of PEMFC. As seen in Figure 8, the proposed model shows considerably good performance during peak load demand periods such as t=2780 s and t=3100 s in testing of ANN-PEMFC model.

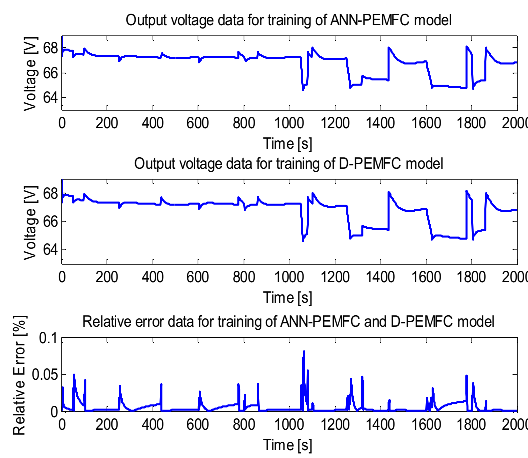

Fig. 6. Output voltage data for training of ANN-PEMFC and D- PEMFC models (t=0 to 2000 s)

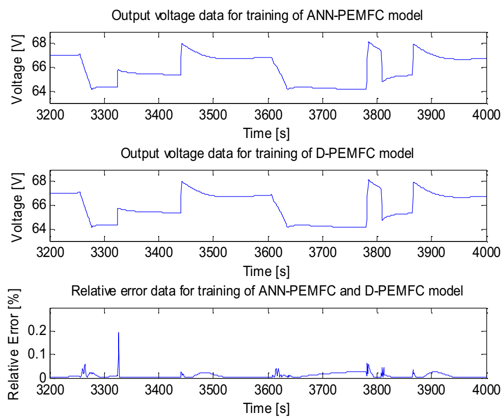

Fig. 7. Output voltage data for training of ANN-PEMFC and D- PEMFC models (t=3200 to 4000 s)

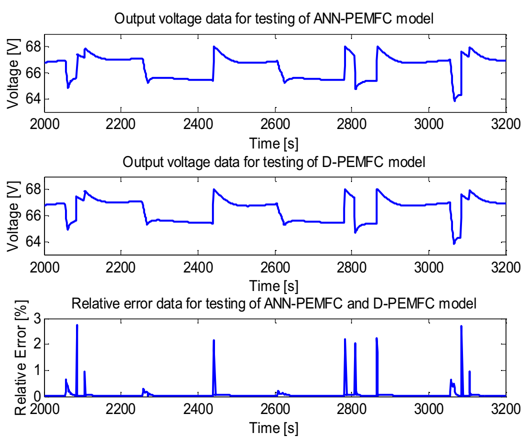

Fig. 8. Output voltage data for validation of ANN-PEMFC and D- PEMFC models

5. Conclusion

In order to model PEMFCs, an ANN based model is proposed in this study. The proposed ANN model needs only two parameters which are the voltage and the current data. The simulation results indicate that the proposed ANN model can predict the stack voltage successfully. It has good prediction accuracy and small relative error. Despite of sudden load changes, the proposed ANN-PEMFC model yields accurate prediction. Consequently, it is a more suitable model for hybrid vehicle and hybrid power generation system. Future work will on different artificial intelligence techniques such as fuzzy logic and ANFIS. Moreover, the proposed model performance can be tested using the real fuel cell parameters.

7. References

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